Technical Sciences
Academy of Romania
www.jesi.astr.ro

Journal of Engineering Sciences and Innovation
Volume 11, Issue 2 / 2026, p. 189 - 214

C. Chemical Engineering, Materials Science and Engineering

Received ***04 December 2025*** *Accepted* ***11 May 2026***
Received in revised form ***12 March 2026***

Multivariate analysis and prediction of the mechanical performance of mortars with old plaster waste

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Abstract. Given the increasing need for sustainable solutions and the valorization of construction and demolition waste, this article proposes an innovative approach focused on advanced analysis of the composition and mechanical performance of cement-lime mortar types in which aggregates, or cement were partially replaced with old plaster waste. The core of the study is the application of Principal Component Analysis (PCA) and the Random Forest Regression algorithm to interpret and predict the behavior of mortars based on their composition and key mechanical properties, such as compressive strength, tensile strength, adhesion to the substrate, consistency, apparent density, and segregation tendency. In the first stage, PCA was used to reduce the complexity of the dataset by grouping the variables into two main components, thus facilitating performance comparisons between mortars with properties expressed in different units of measurement. This method highlighted the essential relationships between the physical-mechanical properties and the composition of the materials. In the second stage, based on the PCA results, a Random Forest Regression algorithm was implemented to predict the flexural tensile strength and compressive strength at 7, 14, and 28 days. The predictions were then compared against the results of the mechanical tests. Among these, the predictions for strength at 28 day showed the closest values with the measured ones, with differences ranging from 3% to 14% below the measured results. This indicates the presence of a value reserve that could be considered in the practical design and application of these alternative mortars.

Keywords: old plaster waste, sustainable development, statistical analysis, strength prediction

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1. Introduction

Sustainable development gained prominence in the 1970s amid rising concerns about pollution and environmental degradation. Since then, the construction sector – responsible for nearly 40% of global waste, resource use, and carbon emissions – has been a major focus of sustainability research. A key strategy involves recycling construction waste into building materials, an approach essential for reducing the industry's environmental impact [[1], [2]]. A wide range of by-products and waste streams – including fly ash, slag, recycled concrete, rubber, glass, ceramic debris, and agricultural residues – have demonstrated potential for reuse in construction, either as aggregate replacements or as partial substitutes for cement. Such practices play a critical role in reducing the sector's overall environmental footprint [[3]]. Among the most pressing challenges is the management of plaster mortar waste from aging buildings, particularly in the context of the increasing frequency of façade restorations. In certain projects, this material can constitute up to 100% of the total waste generated. Owing to their well-defined composition, plaster mortars are especially suitable for reuse in new mortar formulations, both for modern construction and the preservation of historic structures, thereby delivering substantial environmental benefits [[4]].

Random Forest and Principal Component Analysis (PCA) have emerged as powerful analytical approaches increasingly applied in mortar research. These methods enable the classification of mortars into distinct compositional or performance categories and enhance the ability to predict their behavior across both microscopic and macroscopic scales. By integrating machine-learning algorithms with multivariate statistical techniques, Random Forest and PCA provide valuable insights into the relationships between raw material composition, microstructural evolution, and the resulting mechanical and durability properties as it can be observed in the following state-of-the-art analysis [[5]-[24]].

Liu et al. [5] focused on monitoring the early hydration process of mortars using embedded PZT sensors. Principal Component Analysis (PCA) enabled a clear differentiation between the various stages of early hydration by correlating the PZT signal responses with the compressive strength development. This approach also significantly reduced the number of variables required for accurate hydration monitoring. Almeida et al. [6] aimed to identify binder types in historic mortars based on Energy Dispersive Spectroscopy (EDS) data. The application of PCA successfully distinguished between lime-based and pozzolanic mortars, providing a clear separation of binder types and enhancing the accuracy of material characterization in heritage structures. Dilaria et al. [7] analyzed mortars from the archaeological site of Pompeii to reconstruct the chronological sequence of construction phases. PCA effectively grouped the samples into distinct phases, supporting architectural stratigraphy and contributing to the historical understanding of ancient building techniques. Pelosato et al. [8] investigated the mineralogical composition and microstructure of Venetian mortars from the 16th century. PCA revealed strong correlations between mineralogical constituents and microstructural features, enabling the identification of mortar recipes specific to the historical period and construction practices of that era. Santos et al. [9] examined mortars collected from various Portuguese monuments to identify regional variations in lime sources and mortar composition. PCA analysis revealed clear regional differentiation patterns, showing a strong correlation between local limestone sources and the physical properties of the mortars used. Rossi et al. [10] analyzed the influence of recycled aggregates on the physical and mechanical behavior of mortars. PCA efficiently separated mortars containing recycled aggregates from conventional ones, demonstrating how varying proportions of recycled materials directly affect both compressive strength and porosity. Marques et al. [11] explored the impact of supplementary cementitious materials on the performance of hydraulic lime mortars. PCA showed that the incorporation of secondary materials such as fly ash and slag significantly altered mechanical strength and water absorption characteristics, allowing for better optimization of material formulations. Pereira et al. [12] focused on optimizing lime–cement–pozzolan combinations to improve mortar performance. PCA was instrumental in identifying the most effective component ratios, leading to superior mechanical properties and enhanced durability in the resulting mortars. Fiorentino et al. [13] conducted a comprehensive chemical and physical analysis of historical mortars from Mediterranean sites. PCA demonstrated strong correlations between chemical composition and physical properties, facilitating a reliable classification of mortars according to their geographic origin.Gomes et al. [14] examined self-healing mortars incorporating bacterial additives. PCA analysis effectively differentiated these innovative mortars from conventional formulations, emphasizing the significant influence of porosity and hydration products on their self-healing behavior and overall performance. The collective findings from the analyzed studies demonstrate that Principal Component Analysis (PCA) serves as a powerful and versatile tool for understanding and interpreting the complex behavior of mortars across diverse contexts – ranging from historical materials to innovative, sustainable formulations. PCA effectively reduces the number of variables required to describe mortar properties while preserving the essential structural and compositional patterns. It enables clear differentiation of mortars based on binder type, aggregate composition, geographical origin, or historical period, while simultaneously identifying the most influential parameters governing mechanical strength, hydration behavior, microstructure, and durability. Furthermore, PCA has proven effective in monitoring early-age hydration and maturation processes, revealing strong correlations between microstructural evolution and mechanical performance. By highlighting the relationships between chemical and mineralogical composition and physical properties such as porosity, water absorption, and strength, PCA aids in optimizing binder-aggregate-additive ratios for improved performance. It also successfully distinguishes novel mortars – such as those incorporating recycled materials or self-healing agents – from conventional formulations, emphasizing functional advancements. Overall, PCA provides an intuitive, data-driven framework for visualizing and interpreting multivariate datasets, with outcomes that consistently align with physical and chemical analyses, thereby reinforcing its reliability and predictive relevance in mortar research.

Zhang et al. [15] developed machine learning models to predict the compressive strength of magnesium–phosphate cement incorporating various industrial solid wastes such as fly ash and silica fume. The study explored several input variables – including material ratios, water-to-solid ratio, and different additives – while applying model optimization techniques to enhance predictive accuracy. The optimized ensemble models produced predictions that closely matched experimental results, with only minor deviations observed when mortar compositions extended beyond the range of the training dataset. Gayathri et al. [16] Gayathri and co-authors conducted a comparative analysis between several machine learning algorithms – Artificial Neural Networks (ANN), Random Forest (RF), Gradient Boosting, and others – using experimental mortar datasets. Their methodology included clear descriptions of data preprocessing, train–test partitioning, and cross - validation. Among the tested models, RF and Gradient Boosting consistently achieved the highest accuracy, yielding predictions closely aligned with measured compressive strengths, except at very early ages or for atypical mix compositions. Kong et al. [17] compiled a dataset of 204 recycled-powder mortar samples to compare the performance of advanced ensemble algorithms including XGBoost, RF, LightGBM, and AdaBoost. The study emphasized feature selection and hyperparameter optimization to refine model reliability. Results showed that gradient-boosting-based ensembles achieved the best predictive accuracy overall, while RF demonstrated robust performance and good generalization. However, predictive accuracy declined for highly novel mix designs not represented in the training data. Katatchambo et al. [18] evaluated traditional regression techniques, Artificial Neural Networks, and nonlinear ensemble methods to predict the strength of geopolymer mortars containing different slags and chemical activators. The research validated models across various curing times to capture temporal effects on strength development. The findings indicated that nonlinear models – such as ANN and ensemble-based approaches – significantly outperformed simple regression models. Nonetheless, small or highly heterogeneous datasets led to greater discrepancies between predicted and experimental strength values, highlighting the importance of dataset consistency. Kurt et al. [19] Kurt and his team introduced a comprehensive machine learning framework for predicting the mechanical performance of geopolymer mortars. The framework incorporated feature engineering, feature selection, and comparative evaluation of multiple algorithms. The study provided practical guidelines for building effective data pipelines. Models such as Random Forest accurately reproduced experimental strength trends, with substantial error reductions observed after introducing key geopolymer-specific input features and implementing thorough data cleaning. Kurniati et al. [20] presented a series of case studies applying machine learning to predict mortar strength, emphasizing the importance of data preprocessing, curing age (7, 14, and 28 days), and mix composition parameters. Random Forest and other algorithms were evaluated across different datasets. The results revealed that predictions at 7 days were the least accurate due to incomplete hydration, whereas predictions at 14 and 28 days closely matched experimental results. These findings underscored the necessity of including curing age as a critical predictive variable in mortar modeling. Upreti et al. [21] developed both ANN and

Random Forest models to predict the compressive, tensile, and flexural strengths of mortars. They conducted a detailed comparison of model accuracy and interpretability, highlighting the advantages of RF in practical applications. After optimization, RF consistently exhibited smaller deviations from experimental results than ANN and demonstrated strong agreement between predicted and actual values across all tested mechanical properties. Yilmaz et al. [22] Yilmaz and collaborators conducted an extensive study analyzing hundreds of mortar and geopolymer samples to benchmark the generalization performance of Random Forest and other machine learning algorithms. The study demonstrated that models trained on large and diverse datasets achieved excellent predictive accuracy and generalization, with minimal discrepancies between predicted and measured strengths. However, accuracy decreased when testing involved new compositions not adequately represented in the training dataset, highlighting the need for broader data coverage. Poudel et al. [23] applied Random Forest, Gaussian Process Regression, and XGBoost algorithms to predict the mechanical properties of mortars incorporating mine-tailing wastes. The research placed strong emphasis on model validation and feature-importance analysis. The models achieved high R^2 values on internal validation sets, and the largest errors occurred at extreme substitution ratios. Nonetheless, well-tuned modeling pipelines and robust cross-validation procedures effectively minimized bias and improved overall predictive reliability. Fathy et al. [24] carried out a recent comparative analysis involving several advanced regression and ensemble learning algorithms – XGBoost, Random Forest, M5P, and related models – applied across multiple mortar datasets. The study found that all models produced competitive accuracy levels. Gradient boosting algorithms slightly outperformed RF in terms of precision but at the expense of reduced interpretability. The authors emphasized that rigorous cross-validation is essential to obtain unbiased performance estimates and to ensure the robustness of predictive modeling in mortar research.

The reviewed studies collectively demonstrate that Random Forest and ensemble-based algorithms such as XGBoost, LightGBM, and AdaBoost are highly effective tools for predicting the mechanical strength of mortars. These models consistently outperform simpler approaches, including basic neural networks, due to their robustness, interpretability, and adaptability to diverse datasets. While boosting techniques can offer marginal gains in predictive accuracy, Random Forest remains particularly valuable for its balance between performance and explainability. However, prediction accuracy varies with curing age – results at early stages (around 7 days) tend to be less precise because of the incomplete development of the cementitious matrix and the non-linear evolution of material properties; accuracy improves significantly at later ages (14–28 days). Furthermore, the quality of data preprocessing – including outlier treatment, normalization, age-related transformations, and feature selection – plays a decisive role in reducing model error and improving generalization. Interpretability methods such as feature importance ranking and SHAP analysis consistently highlight key influencing variables – cement content, water-to-binder ratio, apparent density, and recycled material percentage – which align well with established physico-chemical principles. Overall, these findings underline the practical potential of machine learning models to provide fast and reliable estimations of mortar performance, offering a means to reduce the need for extensive destructive testing by leveraging measurable input parameters.

2. Materials and Methods

All materials employed in the experimental program complied with relevant regulatory standards [[25], [26], [27]]. By examining the reuse of plaster mortar waste, this study seeks to identify sustainable approaches that can substantially reduce the environmental burden of construction and demolition activities, thereby fostering a circular economy in the building sector.

The old plaster waste used in the experimental program was collected during the renovation of a historic building in Cluj-Napoca, Romania, which involved the complete removal of the deteriorated exterior plaster. The plaster waste was carefully extracted directly from the brick substrate of the façade under restoration. After collection, it was meticulously separated from other construction debris and classified into distinct grades to facilitate its reuse as an aggregate substitute in plaster mortar formulations.

Project documentation for the restored building indicated that the original exterior plaster mortars consisted of cement and lime binders. The sorting and preparation of the recovered waste were carried out in the Building Materials Testing Laboratory of the Faculty of Civil Engineering, Technical University of Cluj-Napoca, ensuring its suitability for experimental applications.

The present article builds upon the studies reported in [[3], [4]]; therefore, the materials, preparation methods, and procedures for assessing mechanical strengths, together with the corresponding numerical values, are described in accordance with those earlier works. The mortar mix designs investigated are presented in Table 1:

Table 1. Studied recipes.

No.	Types of recipes	Recipes details
1	CS III R.S	Reference mix design for CS III class mortar, a cement–lime-based mortar, type M 50 T, prepared in accordance with SR EN 998 [[25], [26]];
2	CS I lime	Mix design for CS I class mortar, lime-based mortar, type M 4 T, prepared in accordance with SR EN 998 [[25], [26]];
3	CS IV cement	Mix design for CS IV class mortar, cement-based mortar, type M 100 T, prepared in accordance with SR EN 998 [[25], [26]];
4	CS III 10% aggregates	Mix design in which 10% of the aggregate content from the reference mix (CS III R.S) was replaced with old plaster waste;
5	CS III 15% aggregates	Mix design in which 15% of the aggregate content from the reference mix (CS III R.S) was replaced with old plaster waste;
6	CS III 30% aggregates	Mix design in which 30% of the aggregate content from the reference mix (CS III R.S) was replaced with old plaster waste;
7	CS III 45% aggregates	Mix design in which 45% of the aggregate content from the reference mix (CS III R.S) was replaced with old plaster waste;
8	CS III 5% cement	Mix design in which 5% of the cement content from the reference mix (CS III R.S) was replaced with old plaster waste;
9	CS III 10% cement	Mix design in which 10% of the cement content from the reference mix (CS III R.S) was replaced with old plaster waste.

In order to perform principal component analysis and random forest regression (for predicting mechanical behaviour of the mortars) limeious data was used as described in Table 2:

Table 2. Main data used for performing analysis and prediction behaviour of the mortars.

Type of Analysis	Data used for analyses/ prediction	State of the mortar (Fresh/ Hardened)	Testing intervals [days]
PCA (principal component analysis)	Composition of the recipe	N.A.	N.A.
	Apparent density	Fresh	N.A.
		Hardened	7, 14, 28
	Consistency	Fresh	N.A.
	Segregation tendency	Fresh	N.A.
	Bending strength	Hardened	7, 14, 28
	Compressive strength	Hardened	7, 14, 28
	Adhesion to the support layer	Hardened	7, 14, 28
RF (random forest regression)	Composition of the recipe	N.A.	N.A.
	Apparent density	Hardened	7, 14, 28
	Bending strength	Hardened	7, 14, 28
	Compressive strength	Hardened	7, 14, 28

2.1. Principal component analysis

Principal Component Analysis (PCA) is an advanced statistical technique employed to investigate and compare the characteristics of systems described by variables with distinct measurement units. This method highlights intrinsic relationships and distinctions within complex datasets, thereby enabling a more effective analysis and classification – an outcome often unattainable through conventional approaches [[28]].

Principal Component Analysis is widely used in mortar research to reduce the dimensionality of complex datasets while retaining the main patterns of variation. PCA supports advanced statistical analysis, improves interpretability, and facilitates the optimization of mortar formulations for enhanced mechanical performance and durability by highlighting the most influential parameters and providing intuitive graphical representations [[29], [30], [31], [32], [33]].

In the reviewed studies, PCA was applied to extract and condense the most relevant variables from multidimensional data obtained through mechanical testing, Nuclear Magnetic Resonance (NMR) spectroscopy, and microstructural analyses. Fechete et al. [[29]] demonstrated that PCA, combined with multilayer neural network analysis, efficiently distinguishes microstructural patterns in cement-based materials by interpreting spectral and relaxation data. Similarly, Asteris et al. [[30]] highlighted PCA's role in optimizing input parameters before machine learning modeling, improving the accuracy of compressive strength prediction. Other works, such as those by Haozheng et al. [[31], [33]] and Renhong et al. [[32]], used PCA to correlate curing age, fractal characteristics, and microstructural parameters with mechanical and impermeability properties. Collectively, these studies show that PCA enhances data clarity, reduces redundancy, and enables the identification of key factors governing mortar performance – serving as a bridge between experimental data and predictive modeling.

2.2. Random forest regression

The Random Forest (RF) algorithm, developed by Breiman in 2001 [[34]], can be defined as an ensemble of structured decision trees used for classification and/or regression. Each tree is built on a random subset of the training set using selection with replacement (bagging). This means that selected samples are not removed from the dataset, allowing some samples to be chosen multiple times while others may not be selected at all in a new set. This resampling method improves accuracy by reducing the limeiance of classification errors [[30]]. The predictions of each individual regression tree are averaged to generate the outcome [[35]].
The bagging technique creates new training sets by resampling the original dataset *n* times (where *n* represents the number of samples in the initial training set), randomly and with replacement. In other words, a selected sample is not removed from the dataset, which means that some samples may appear several times while others may not be included at all in a new set [[36]]. The bagging technique improves classification accuracy by reducing the variance of classification errors, as it helps control classifier instability. In this context, "instability" refers to the fact that a small change in the training samples can lead to significant changes in classifier accuracy. To combine classifier decisions, majority voting is used, with each classifier contributing one equally weighted vote. In the case of a tie, the decision is made either based on predefined rules or at random. The RF algorithm uses the Gini impurity index to build multiple decision trees [[37]].
During tree construction, RF randomly selects only a subset of input features (bands) at each split node, yet each tree can grow fully without requiring a pruning process. It is important to note that RF is computationally efficient, as it relies on only a subset of input features, and the absence of pruning further optimizes performance. The computation time is on the order of $T\sqrt{M}N log_2\{N\}$, where T is the number of trees, N is the number of training samples, and M is the number of bands used in each division [[34]]. Additionally, if no separate test set is available, the out-of-bag (OOB) method is applied. For each new training set produced, 33% of the samples are left out randomly (OOB samples). The remaining samples (in-the-bag samples) are used in building the decision trees. To predict accuracy, votes are counted for each sample whenever it belongs to the OOB set. The final label is determined by majority voting. Only about 33% of the constructed trees are allowed to vote for each case. OOB error estimates have been shown to be unbiased in numerous tests [[34]]. The number of features used at each split is defined by the user, but this parameter does not significantly affect the algorithm. Majority voting is applied to aggregate the decisions of the classifiers in the ensemble. A detailed explanation of the Random Forest algorithm can be found in Breiman's study [[34]], while Gislason et al. [[38]],

Şahin et al. [[39]], Panagiotis et al. [[40]], Zhiqiang [[41]], Rajakumaran et al. [[42]], and Majdi et al. [[43]] also provide summaries including numerous considerations on the functioning of the algorithm and its application to different types of mortars or concretes, primarily using training sets based on experimental data and results available in the literature.

For the present study, the Python programming language [[44]] was used to employ the Random Forest Regression algorithm [[34]] to predict flexural tensile strength and compressive strength both for previously analyzed mortars (to enable comparisons with obtained values) and for new mortar formulations not yet investigated (CS III 60% aggregates and CS III 20% cement). As input data (see Table 2), all available characteristics prior to mechanical testing of mortar samples were used, namely the quantities of cement, lime, old plaster, wastewater, aggregates, the apparent density in the hardened state, as well as the mechanical strengths obtained from tests performed at 7, 14, and 28 days (flexural tensile and compressive strength).

3. Results

3.1. Principal component analysis

The datasets introduced for PCA are summarized in Table 3 – Table 5, corresponding to the properties determined for the investigated mortar types. Specifically, Table 3 presents the analyzed formulations, Table 4 reports the test results for fresh mortars, and Table 5 reports the results for hardened mortars. Prior to PCA application, all data were consolidated into a single dataset to ensure comprehensive and consistent processing.

Table 3. Composition of the mixes for all testing intervals (7, 14, and 28 days).

No.	**Recipe**	**Cement 52.5 R [kg]**	**Sand [kg]**	**Lime [kg]**	**Old plaster waste [kg]**	**Water [l]**
1	CS III R. S	275	1450	110	0	311.43
2	CS I lime	0	1550	500	0	335.71
3	CS IV cement	385	1550	0	0	297.14
4	CS III 10% aggregates	275	1305	110	145	325.71
5	CS III 15% aggregates	275	1232.5	110	217.5	331.43
6	CS III 30% aggregates	275	1015	110	435	342.14
7	CS III 45% aggregates	275	797.5	110	652.5	357.14
8	CS III 5% cement	261.25	1450	110	13.75	297.86

9	CS III 10% cement	247.5	1450	110	27.5	332.14

Table 4. Experimental results for Fresh Mortars.

No.	**Recipe**	**Apparent density ρ_a [kg/ m^3]**	**Consistency d_{med} [mm]**	**Segregation tendency S [cm^3]**
1	CS III R. S	275	1450	110
2	CS I lime	0	1550	500
3	CS IV cement	385	1550	0
4	CS III 10% aggregates	275	1305	110
5	CS III 15% aggregates	275	1232.5	110
6	CS III 30% aggregates	275	1015	110
7	CS III 45% aggregates	275	797.5	110
8	CS III 5% cement	261.25	1450	110
9	CS III 10% cement	247.5	1450	110

Table 5. Experimental results for Hardened Mortars.

No.	**Recipe**	**Apparent density, ρ_a [kg/ m^3]**	**Compressive strength, f_{cm} [N/ mm^2]**	**Bending strength, $f_{ctm,fl}$ [N/ mm^2]**	**Adhesion to the support layer f_u [N/ mm^2]**
1.1	CS III R. S 7 days	2210.16	3.41	12.69	-
1.2	CS III R. S 14 days	2168.62	3.66	16.04	-
1.3	CS III R. S 28 days	2043.88	4.34	21.60	0.475
2.1	CS I lime 7 days	1781.00	0.35	0.29	-
2.2	CS I lime 14 days	1794.00	0.43	0.33	-
2.3	CS I lime 28 days	1800.00	0.33	0.34	0.1
3.1	CS IV cement 7 days	2196.00	3.90	14.63	-
3.2	CS IV cement 14 days	2146.00	3.97	19.35	-
3.3	CS IV cement 28 days	2135.00	3.98	24.25	0.83
4.1	CS III 10% aggregates 7 days	1989.00	2.55	11.35	-

No.	**Recipe**	**Apparent density, ρ_a [kg/ m^3]**	**Compressive strength, f_{cm} [N/ mm^2]**	**Bending strength, $f_{ctm,fl}$ [N/ mm^2]**	**Adhesion to the support layer f_u [N/ mm^2]**
4.2	CS III 10% aggregates 14 days	1957.00	3.23	13.20	-
4.3	CS III 10% aggregates 28 days	1914.45	3.94	13.66	0.413
5.1	CS III 15% aggregates 7 days	1976.56	2.30	9.88	-
5.2	CS III 15% aggregates 14 days	1948.05	2.88	12.19	-
5.3	CS III 15% aggregates 28 days	1894.66	3.49	13.38	0.385
6.1	CS III 30% aggregates 7 days	1916.41	2.27	11.07	-
6.2	CS III 30% aggregates 14 days	1885.94	3.98	15.37	-
6.3	CS III 30% aggregates 28 days	1844.40	4.23	15.83	0.343
7.1	CS III 45% aggregates 7 days	1960.16	2.54	8.46	-
7.2	CS III 45% aggregates 14 days	1926.82	2.74	10.05	-
7.3	CS III 45% aggregates 28 days	1811.46	3.32	13.29	0.313
8.1	CS III 5% cement 7 days	2025.26	3.41	11.91	-
8.2	CS III 5% cement 14 days	2012.89	3.66	14.95	-
8.3	CS III 5% cement 28 days	1969.40	4.34	16.43	0.419
9.1	CS III 10% cement 7 days	2134.11	3.05	8.19	-
9.2	CS III 10% cement 14 days	2072.40	3.90	11.76	-
9.3	CS III 10% cement 28 days	1955.08	4.31	15.81	0.38

Thus, in the present case, after analyzing all the data from Table 33Table 4. Experimental results for Fresh Mortars.
, and Table 5, and following all the previously described steps, the graphical representation of all characteristics grouped into two principal components was obtained, as shown in Fig. 1.
Following the PCA analysis presented in Fig. 1, five important and relevant zones can be observed regarding the graphical positioning of the studied mixtures. These well-defined delimitations suggest, even from the initial stage, the differences between the main characteristics analyzed.

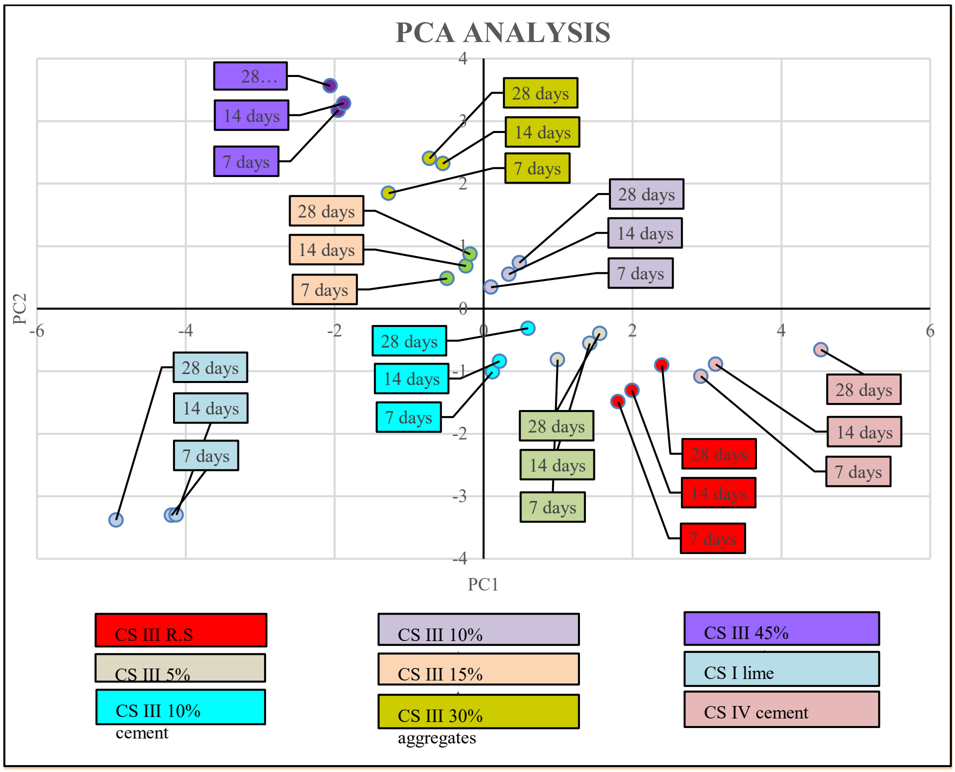


Fig. 1. PCA analysis results for the studied mixes.

3.2. Random forest regression

The data sets introduced for Random Forest regression are summarized in Table 6 – Table 7, corresponding to the properties determined for the investigated mortar types, specifically the input data for compressive strength and bending strength, respectively.

Table 6. Input data for compressive strength prediction using the Random Forest Regression algorithm.

Recipe	Compressive strength, f_{cm} [N/mm²]	Apparent density, ρ_a [kg/m³]	Cement 52.5 R [kg]	Sand [kg]	Lime [kg]	Old plaster waste [kg]	Water [l]
CS III R.S 7 days	12.69	2210.16	275	1450	110	0.00	311.43
CS III R.S 14 days	16.04	2168.62	275	1450	110	0.00	311.43
CS III R.S 28 days	21.60	2043.88	275	1450	110	0.00	311.43
CS IV cement 7 days	14.63	2196.00	385	1550	0	0.00	297.14
CS IV cement 14 days	19.35	2146.00	385	1550	0	0.00	297.14

Recipe	**Compressive strength, f_{cm} [N/mm^2]**	**Apparent density, ρ_a [kg/m^3]**	**Cement 52.5 R [kg]**	**Sand [kg]**	**Lime [kg]**	**Old plaster waste [kg]**	**Water [l]**
CS IV cement 28 days	24.25	2135.00	385	1550	0	0.00	297.14
CS III 10% aggregates 7 days	11.35	1989.00	275	1305	110	145.00	325.71
CS III 10% aggregates 14 days	13.20	1957.00	275	1305	110	145.00	325.71
CS III 10% aggregates 28 days	13.66	1914.45	275	1305	110	145.00	325.71
CS III 15% aggregates 7 days	9.88	1976.56	275	1232.5	110	217.50	331.43
CS III 15% aggregates 14 days	12.19	1948.05	275	1232.5	110	217.50	331.43
CS III 15% aggregates 28 days	13.38	1894.66	275	1232.5	110	217.50	331.43
CS III 30% aggregates 7 days	11.07	1916.41	275	1015	110	435.00	342.14
CS III 30% aggregates 14 days	15.37	1885.94	275	1015	110	435.00	342.14
CS III 30% aggregates 28 days	15.83	1844.40	275	1015	110	435.00	342.14
CS III 45% aggregates 7 days	8.46	1960.16	275	797.5	110	652.50	357.14
CS III 45% aggregates 14 days	10.05	1926.82	275	797.5	110	652.50	357.14
CS III 45% aggregates 28 days	13.29	1811.46	275	797.5	110	652.50	357.14
CS I lime 7 days	0.29	1781.00	0	1550	500	0.00	335.71
CS I lime 14 days	0.33	1794.00	0	1550	500	0.00	335.71
CS I lime 28 days	0.34	1800.00	0	1550	500	0.00	335.71
CS III 5% cement 7 days	11.91	2025.26	261.25	1450	110	13.75	297.86
CS III 5% cement 14 days	14.95	2012.89	261.25	1450	110	13.75	297.86
CS III 5% cement 28 days	16.43	1969.40	261.25	1450	110	13.75	297.86
CS III 10% cement 7 days	8.19	2134.11	247.5	1450	110	27.50	332.14
CS III 10% cement 14 days	11.76	2072.40	247.5	1450	110	27.50	332.14
CS III 10% cement 28 days	15.81	1955.08	247.5	1450	110	27.50	332.14

Table 7. Input data for bending strength prediction using the Random Forest Regression algorithm.

Recipe	Bending strength $f_{ctm,\,fl}$ [N/mm^2]	Apparent density ρ_a [kg/m^3]	Cement 52.5 R [kg]	Sand [kg]	Lime [kg]	Old plaster waste [kg]	Water [l]
CS III R.S 7 days	3.41	2210.16	275	1450	110	0.00	311.43
CS III R.S 14 days	3.66	2168.62	275	1450	110	0.00	311.43
CS III R.S 28 days	4.34	2043.88	275	1450	110	0.00	311.43
CS IV cement 7 days	3.9	2196.00	385	1550	0	0.00	297.14
CS IV cement 14 days	3.97	2146.00	385	1550	0	0.00	297.14
CS IV cement 28 days	3.98	2135.00	385	1550	0	0.00	297.14
CS III 10% aggregates 7 days	2.55	1989.00	275	1305	110	145.00	325.71
CS III 10% aggregates 14 days	3.23	1957.00	275	1305	110	145.00	325.71
CS III 10% aggregates 28 days	3.94	1914.45	275	1305	110	145.00	325.71
CS III 15% aggregates 7 days	2.3	1976.56	275	1232.5	110	217.50	331.43
CS III 15% aggregates 14 days	2.88	1948.05	275	1232.5	110	217.50	331.43
CS III 15% aggregates 28 days	3.49	1894.66	275	1232.5	110	217.50	331.43
CS III 30% aggregates 7 days	2.27	1916.41	275	1015	110	435.00	342.14
CS III 30% aggregates 14 days	3.98	1885.94	275	1015	110	435.00	342.14
CS III 30% aggregates 28 days	4.23	1844.40	275	1015	110	435.00	342.14
CS III 45% aggregates 7 days	2.54	1960.16	275	797.5	110	652.50	357.14
CS III 45% aggregates 14 days	2.74	1926.82	275	797.5	110	652.50	357.14
CS III 45% aggregates 28 days	3.32	1811.46	275	797.5	110	652.50	357.14
CS I lime 7 days	0.35	1781.00	0	1550	500	0.00	335.71
CS I lime 14 days	0.43	1794.00	0	1550	500	0.00	335.71
CS I lime 28 days	0.33	1800.00	0	1550	500	0.00	335.71
CS III 5% cement 7 days	3.05	2025.26	261.25	1450	110	13.75	297.86
CS III 5% cement 14 days	3.9	2012.89	261.25	1450	110	13.75	297.86
CS III 5% cement 28 days	4.31	1969.40	261.25	1450	110	13.75	297.86

Recipe	Bending strength $f_{ctm, fl}$ [N/mm^2]	Apparent density ρ_a [kg/m^3]	Cement 52.5 R [kg]	Sand [kg]	Lime [kg]	Old plaster waste [kg]	Water [l]
CS III 10% cement 7 days	2.23	2134.11	247.5	1450	110	27.50	332.14
CS III 10% cement 14 days	2.33	2072.40	247.5	1450	110	27.50	332.14
CS III 10% cement 28 days	4.03	1955.08	247.5	1450	110	27.50	332.14

The two input data tables (**Table 6** and Table 7) were entered separately into the algorithm depending on the type of strength for which predictions were sought, the program was executed using the Python programming language. Summarizing the calculation algorithm, after entering and analyzing the input data, proper training of the prediction model is required. Thus, 80% of the total data is used for training, while the remaining 20% are employed for predictions, as shown in Fig. 2 and Fig. 3, which results directly from running the program.

In this case as well, according to the PCA analyses, the importance of the input features is determined through complex statistical evaluations that account for variations in the mix compositions and their influence on the resulting mechanical properties.

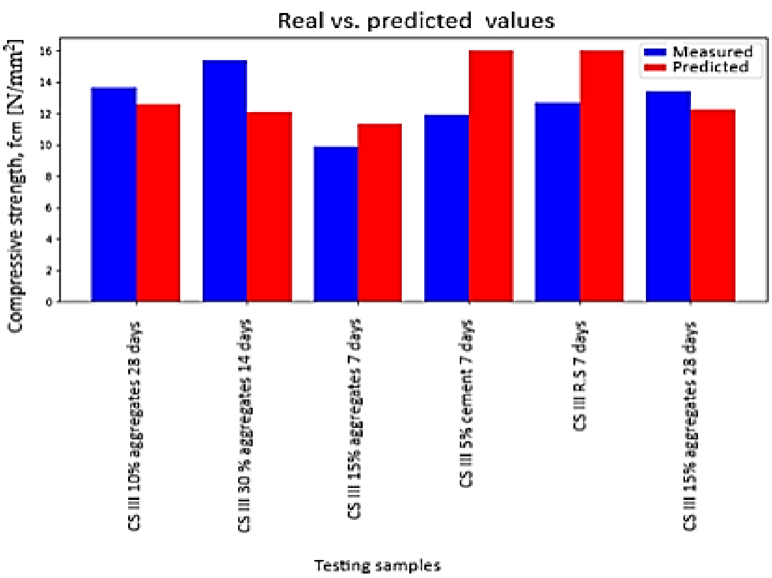


Fig. 2. Comparison between measured and predicted values of compressive strength using Random Forest algorithm for the remaining 20% of the data after training.

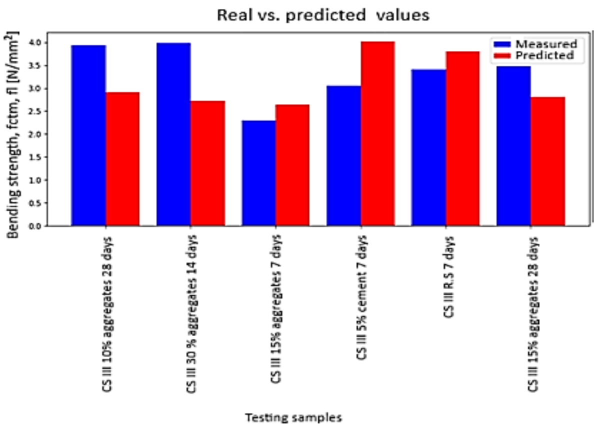


Fig. 3. Comparison between measured and predicted values of bending strength using Random Forest algorithm for the remaining 20% of the data after training.

4. Discussions

4.1. Principal component analysis

In determining the principal components, both for principal component number 1 (PC1) and principal component number 2 (PC2), all features included in the calculation matrix were considered. The importance of these features is shown in Fig. 4 and Fig. 5, where the contribution of each to the overall equation can be observed.

The parameters with the highest importance for PC1 are cement content, lime content, fresh and hardened density, compressive and flexural tensile strengths, and adhesion to the substrate layer whereas sand, segregation tendency or consistency are the parameters with the lowest considered importance. The parameters with the highest importance for PC2 are sand content, lime content, plaster waste content, and fresh density. The other characteristics have a lower level of importance for this component.

Considering the contribution of the parameters in both PC1 and PC2, it can be observed that the mortar samples in which aggregates were partially replaced with plaster waste are positioned in the positive region of the PC2 axis (PC2 > 0) (see Figure 1). In contrast, the mortar samples for which cement was replaced with plaster waste, as well as those without any such waste, are located in the negative region of PC2 (PC2 < 0) as it can be observed from Fig. 1. Regarding their positioning along the PC1 axis, it is observed that mortars with a higher percentage of aggregate replacement using plaster waste, as well as lime-based mortars, are situated in the negative region of the axis (PC1 < 0). Meanwhile, the samples in which cement or a small proportion of aggregates were partially replaced with waste, together with the reference sample (CS III R.S.) and the cement-based mortar (CS IV cement), are found in the positive region of PC1 (PC1 > 0) (see Fig. 1).

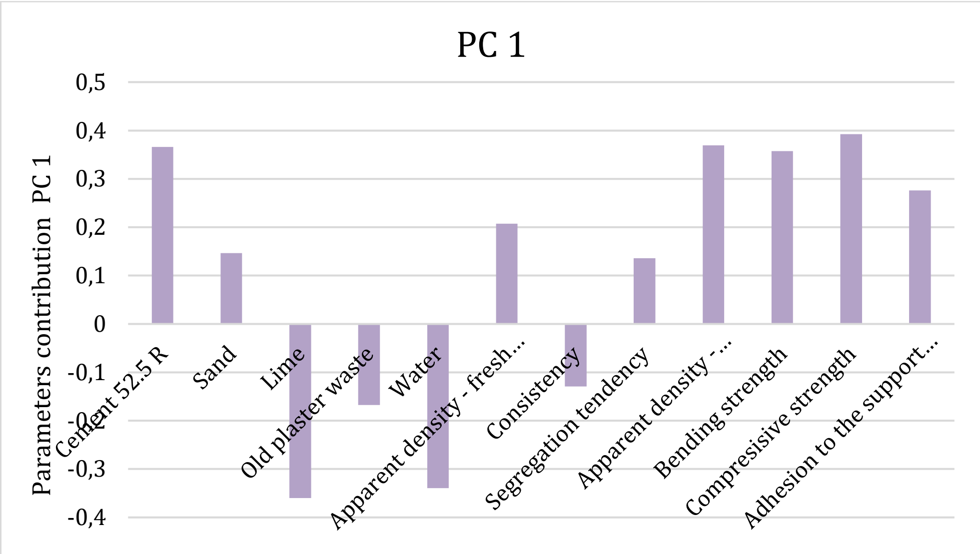


Fig. 4. Parameters contribution in case of PC 1.

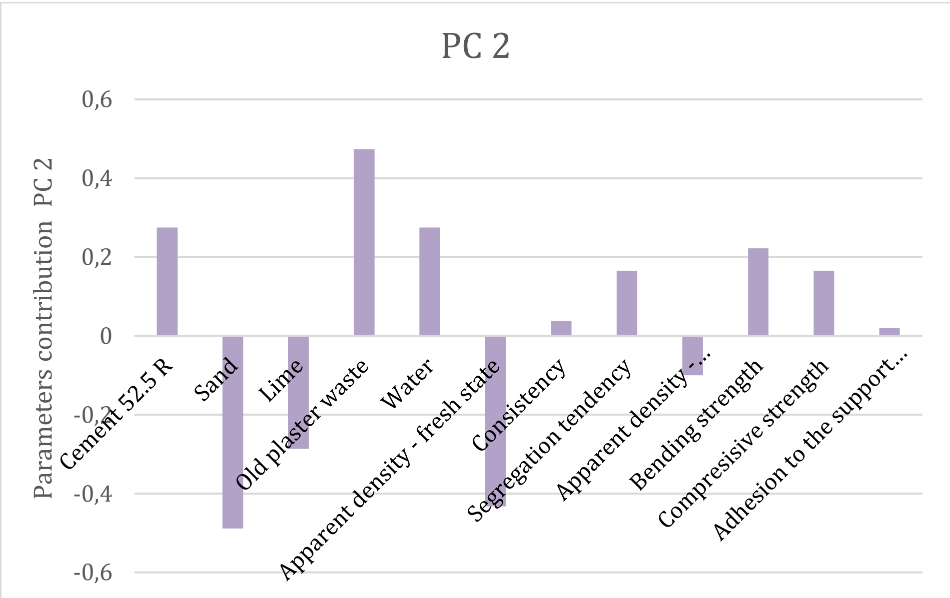


Fig. 5. Parameters contribution in case of PC 2.

Based on the above-mentioned positioning of the results and the five zones described in Figure 1, several interpretations can be drawn. In the top-left area, where the values for the CS III 45% aggregates and CS III 30% aggregates mixes are grouped, a clear differentiation from the other formulations is observed along principal component 2 (PC2), primarily due to the high content of old plaster waste, which leads to increased porosity and reduced mechanical strength. In the central area above the PC1 axis, the CS III 15% aggregates and CS III 10% aggregates mixes are positioned closer to the standard mix, suggesting improved mechanical properties and a balance between core characteristics and potential degradation. In the central area below the PC1 axis, the CS III 5% cement and CS III 10% cement mixes are located even closer to the standard, indicating higher mechanical strengths and more stable performance. The bottom-left zone, where the CS I lime mix is found, shows tightly grouped points that are distinctly separated from the other mortars, particularly from CS IV cement located on the opposite side of the principal component, suggesting that the lime-only mix exhibits a porous structure, slow hydration, and limited mechanical strength. Finally, in the bottom-right region below the PC1 axis, the CS III R.S and CS IV cement mixes are closely positioned, indicating that these formulations achieved the highest strength values across all testing ages.

4.2. Random Forest regression

The complex analyses performed after including all the studied features also lead, in this case, to the determination of their importance in the strength prediction process, as shown in Fig. 6 and Fig. 7.

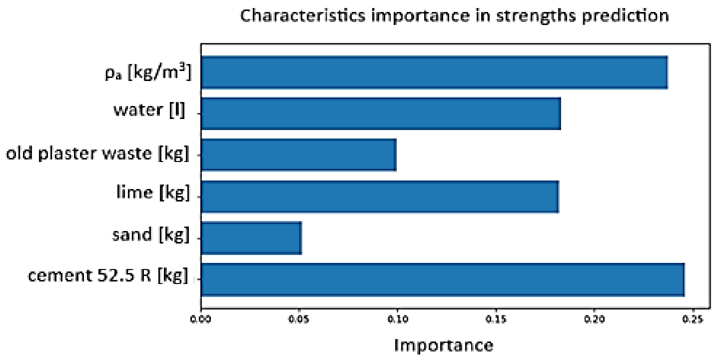


Fig. 6. Influence of the analyzed features on compressive strength prediction by Random Forest regression.

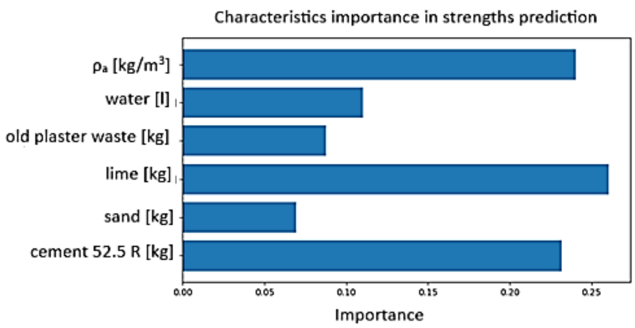
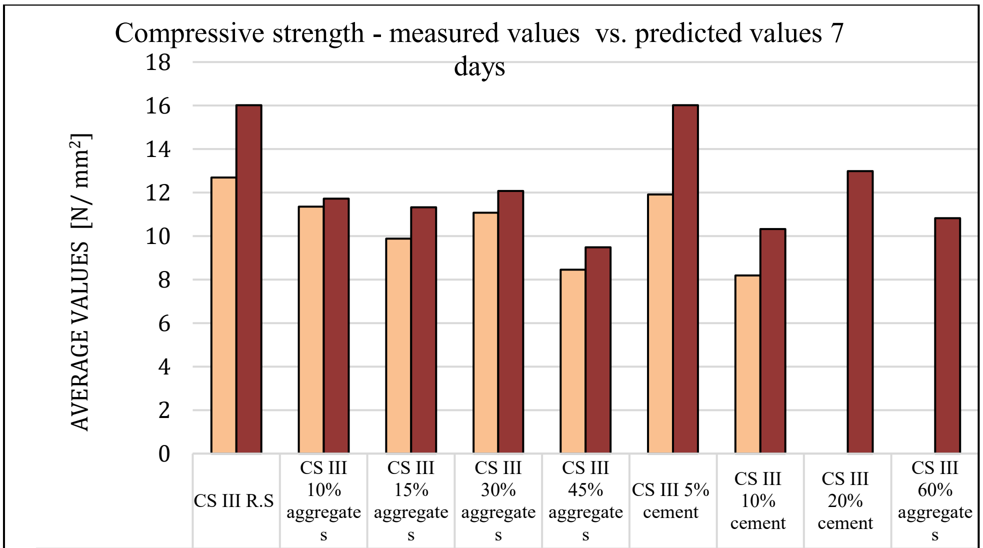


Fig. 7. Influence of the analyzed features on bending strength prediction by Random Forest regression.

According to predictions obtained from Random Forest Regression, the greatest influence on compressive strength prediction is exerted by the cement content and the hardened apparent density, followed by the amounts of water and lime, and then by the quantities of plaster waste and aggregates whereas the greatest influence on flexural tensile strength prediction is exerted by the lime content, hardened apparent density, and cement content, followed by the amounts of water, plaster waste, and aggregates.

Subsequently, using a modern tool based on artificial intelligence, e.g. the prediction program already trained for compressive and flexural tensile strength and tested with promising results (see Fig. 2 and Fig. 3) and characterized by well-defined importance levels for the input parameters, a new file was created containing all mortar characteristics that can be determined prior to mechanical testing and reintroduced as input data. This allows the prediction code to generate comparative values for all analyzed mixes, including predictions for mixes that have not yet been prepared and tested (CS III 60% aggregates, CS III 20% cement) at all ages (7, 14, and 28 days).



	CS III R.S	CS III 10% aggregates	CS III 15% aggregates	CS III 30% aggregates	CS III 45% aggregates	CS III 5% cement	CS III 10% cement	CS III 20% cement	CS III 60% aggregates
Measured values	12,69	11,35	9,88	11,07	8,46	11,91	8,19		
Predicted values	16,02	11,72	11,32	12,08	9,48	16,01	10,32	12,98	10,82

Fig. 8. Comparison between the experimental values vs. predicted values obtained from Random Forrest regression for the compressive strength at 7 days.

According to the results presented in Fig. 8 and Fig. 9, at 7 days after preparation, all predicted values are systematically higher than the measured results. This indicates that predicting compressive or flexural tensile strength at an early age is more challenging because the cement matrix and hydration phases are not fully developed, and the considered parameters evolve during the hardening process. For the same reason, predictions for the CS III 20% cement and CS III 60% aggregates mixes also appear higher than usual. The percentage differences between the two types of values are presented in Table 8.

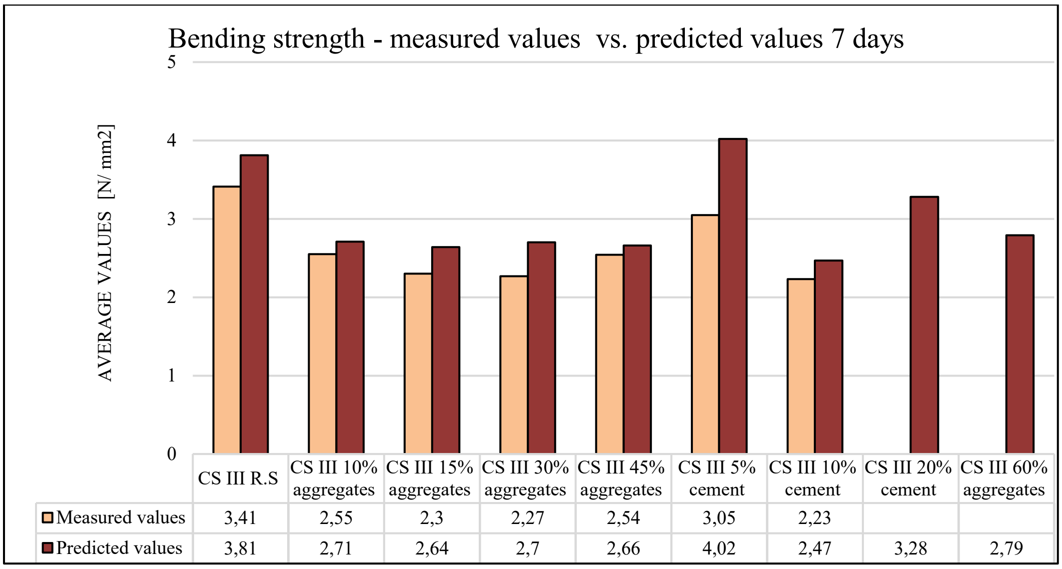


Fig. 9. Comparison between the experimental values vs. predicted values obtained from Random Forrest regression for the bending strength at 7 days.

Table 8. Percentage differences between measured and predicted values for compressive strength and bending strength at 7 days after preparation.

Recipe	Percentage difference for compressive strength [%]	Percentage difference for bending strength [%]
CS III R.S	26.2	11.7
CS III 10% aggregates	3.3	6.3
CS III 15% aggregates	14.6	14.8
CS III 30% aggregates	9.1	18.9
CS III 45% aggregates	12.1	4.7
CS III 5% cement	34.4	31.8
CS III 10% cement	26	10.8

At the age of 7 days, substantial percentage differences can be observed between the predicted and measured values both for compressive and bending strengths, as it is difficult to accurately predict the mechanical behavior of mortar samples at this early stage because the cement matrix is still in an initial phase of hardening, and the main hydration compounds have not yet fully bonded or developed.
According to the results presented in Fig. 10 and 11, at 14 days after preparation, some predicted values are higher than the actual results, while others are lower. However, it should be noted that the differences between the values have decreased compared

to the 7-day age as it can be observed in Table 9 where the percentage differences are presented.

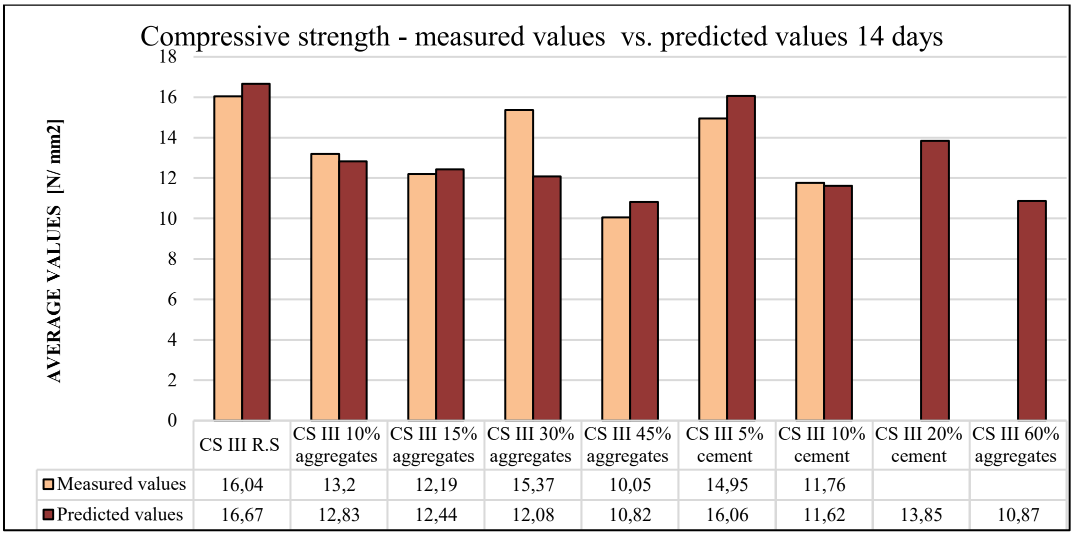


Fig. 10. Comparison between the experimental values vs. predicted values obtained from Random Forrest regression for the compressive strength at 14 days.

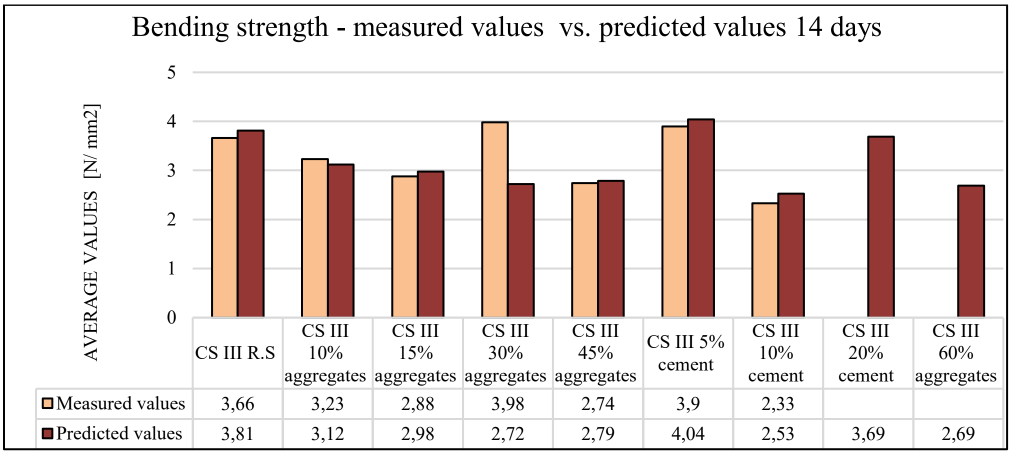


Fig. 11. Comparison between the experimental values vs. predicted values obtained from Random Forrest regression for the bending strength at 14 days.

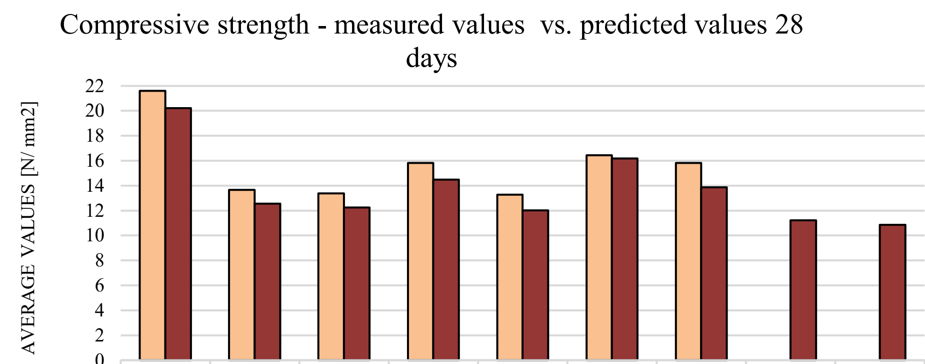
Table 9. Percentage differences between measured and predicted values for compressive strength and bending strength at 14 days after preparation.

Recipe	Percentage difference for compressive strength [%]	Percentage difference for bending strength [%]

CS III R.S	3.9 %	4.1 %
CS III 10% aggregates	-2.8 %	-3.4 %
CS III 15% aggregates	2.1 %	3.5 %
CS III 30% aggregates	-21.4 %	-31.7 %
CS III 45% aggregates	7.7 %	1.8 %
CS III 5% cement	7.4 %	3.6 %
CS III 10% cement	-1.2 %	8.6 %

At 14 days after preparation, it can be observed a decrease in percentage differences between measured and predicted values for both compressive and bending strengths due to the development of the cement matrix and hydration phases that lead to predicted values that are closer to the measured ones. Although, the predicted values for the CS III 20% cement and CS III 60% aggregates mixes still appear higher than usual.

According to Fig. 12 andFig. 13, at 28 days, all predicted values are lower than the actual results (with some differences larger than those at 14 days), a fact explained by the maturation of the cement matrix and the proper development of the hydration phases. This fact is also sustained by results presented in Table 10.



	CS III R.S	CS III 10% aggregates	CS III 15% aggregates	CS III 30% aggregates	CS III 45% aggregates	CS III 5% cement	CS III 10% cement	CS III 20% cement	CS III 60% aggregates
Measured values	21,6	13,66	13,38	15,83	13,29	16,43	15,81		
Predicted values	20,23	12,56	12,25	14,49	12,03	16,17	13,87	11,22	10,86

Fig. 12. Comparison between the experimental values vs. predicted values obtained from Random Forrest regression for the compressive strength at 28 days.

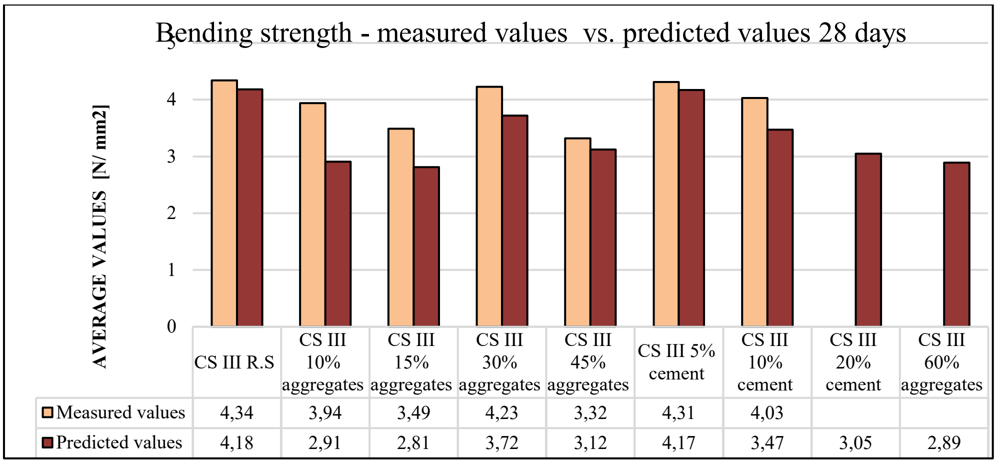


Fig. 13. Comparison between the experimental values vs. predicted values obtained from Random Forrest regression for the bending strength at 28 days.

Table 10. Percentage differences between measured and predicted values for compressive strength and bending strength at 28 days after preparation.

Recipe	Percentage difference for compressive strength [%]	Percentage difference for bending strength [%]
CS III R.S	-6.3 %	-3.7 %
CS III 10% aggregates	-8.1 %	-26.1 %
CS III 15% aggregates	-8.4 %	-19.5 %
CS III 30% aggregates	-8.5 %	-12.1 %
CS III 45% aggregates	-9.5 %	-6.0 %
CS III 5% cement	-1.6 %	-3.2 %
CS III 10% cement	-12.3 %	-13.9 %

At the age of 28 days after preparation all percentage differences between measured and predicted values indicate negative values which means that all predictions were lower than the measurements. This fact can have a positive aspect, since, depending on the purpose of the predictions or the final use of the mortars, there is a value reserve that can be later considered. The predicted values for the CS III 20% cement and CS III 60% aggregates mixes, at this age, show a decrease compared to the lower replacement ratios of aggregates or cement, which continues the downward trend as the amount of plaster waste increases.

5. Conclusion

Considering all the results obtained from both the Principal Component Analysis (PCA) and the Random Forest Regression modelling, several important conclusions can be drawn. The PCA results showed strong consistency between the mechanical strength values and the microscopic determinations, confirming the reliability of this statistical approach. Replacing aggregates in proportions higher than 30–45% was found to significantly alter the cementitious matrix structure, while cement replacement levels of 5–10% produced minimal negative effects and on the mechanical performance. The Random Forest Regression algorithm, implemented in Python, successfully generated predictions close to the experimental results once trained with accurate parameters, demonstrating its robustness and adaptability. Feature importance analysis revealed that compressive strength depends primarily on cement content and apparent density in the hardened state, while flexural strength is mainly influenced by lime content, apparent density, and cement content. Moreover, prediction accuracy improved with curing time, showing a natural alignment with the progressive hydration and strengthening of the cement matrix. For the untested mortar mixes, accurate predictions at 28 days followed the expected trend of decreasing strength with increasing waste content.

The results obtained and the comprehensive analysis performed on the studied mortars highlight that the combination of Principal Component Analysis (PCA) and Random Forest Regression modeling allowed for several key insights: it confirmed the direct relationship between mechanical performance, microstructure, and chemical-mineralogical composition; it enabled the identification of the mechanical behavior of mortars with new cement and aggregate replacement ratios by validating the predictive capability of the system; and it provided a clear understanding of the relative importance of each parameter in overall mortar behavior.

Overall, the integrated use of PCA and Random Forest represents an innovative analytical framework that not only validates experimental findings but also enhances the predictive understanding of cement-lime mortar behavior. This combined approach bridges experimental data and computational intelligence, offering a powerful, data-driven tool for designing sustainable mortars with optimized mechanical and microstructural performance.

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